

Monitoring the Microgravity Environment Quality On-Board the International Space Station Using Soft Computing Techniques

Part I: System Design

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ABSTRACT

This paper presents an artificial intelligence monitoring system developed by the NASA Glenn Principal Investigator Microgravity Services project to help the principal investigator teams identify the primary vibratory disturbance sources that are active, at any moment in time, on-board the International Space Station, which might impact the microgravity environment their experiments are exposed to. From the Principal Investigator Microgravity Services' web site, the principal investigator teams can monitor via a graphical display, in near real time, which event (s) is /are on, such as crew activities, pumps, fans, centrifuges, compressor, crew exercise, platform structural modes, etc., and decide whether or not to run their experiments based on the acceleration environment associated with a specific event.

This monitoring system is focused primarily on detecting the vibratory disturbance sources, but could be used as well to detect some of the transient disturbance sources, depending on the events duration. The system has built-in capability to detect both known and unknown vibratory disturbance sources. Several soft computing techniques such as Kohonen's Self-Organizing Feature Map, Learning Vector Quantization, Back-Propagation Neural Networks, and Fuzzy Logic were used to design the system.

INTRODUCTION

With the International Space Station (ISS) soon to be operational, many of the scientific experiments, which used to be conducted on-board the NASA Space Shuttle orbiters for long duration microgravity conditions will be conducted onboard the ISS, which will allow even longer periods of microgravity. Many of these scientific experiments will require knowledge of the microgravity environment for accurate analysis of the experimental data. The Microgravity Measurement and Analysis Project (MMAP) at NASA Glenn Research Center (GRC), which the Principal Investigator Microgravity Services (PIMS) project is a part of, has the responsibility for measuring, analyzing, and characterizing the microgravity environment for Principal Investigator (PI) teams and providing expertise in microgravity environment assessment.

The PIMS project at the NASA Glenn Research center supports NASA's Microgravity Research Division Principal Investigators (PIs) by providing acceleration data analysis and interpretation for a variety of microgravity carriers such as the Space Shuttle, parabolic aircraft (KC-135), sounding rocket, drop towers, the Russian Mir Space Station, and the International Space Station (ISS). In general, the PIMS project's acceleration data support efforts are to archive and disseminate accelerometer data; to support users interested in the microgravity acceleration environment by

providing information about activities and acceleration sources; to identify acceleration sources related to vehicle systems, experiment hardware, vibration isolation systems, and other systems; to develop data analysis techniques and displays per user requirements; to educate users about the environment and data analysis techniques; to provide standard data interpretation reports; and to characterize the microgravity environment of the ISS in support of PIs.

PIMS has characterized the microgravity environment for various earth orbiting platforms as well as ground based facilities in support of PIs from various science disciplines such as biotechnology, combustion science, fluid physics, materials science, and fundamental physics.

With the advent of the ISS operation, a vast amount of acceleration data is expected to be collected, processed, and analyzed for both the ISS microgravity environment characterization (verification) and scientific experiments. This offers a unique challenge for the task of data analysis. A comprehensive means of examining the collected data to assist in identifying significant acceleration trends and events is needed. To tackle that problem, the NASA Glenn PIMS project is currently developing an artificial intelligence monitoring system, which will show the principal investigator teams in near real time any change in the microgravity environment that might affect their experiments. This Artificial Intelligence (AI) monitoring system will extract, analyze, and interpret the most salient features of the microgravity environment on-board the ISS at any moment, in near real time, as data is downlinked from the ISS for processing. Such a system will help the Principal Investigator (PI) teams monitor the microgravity environment on-board the ISS in order to avoid, whenever possible, any negative impact on their experiments.

The PIMS ISS Microgravity Environment Monitoring System (MEMS) will do the following: 1) detect the current vibratory events on-board the ISS in near real time; 2) classify each known event and assess their relative impact on the environment; 3) identify unknown events, which require characterization. The system will act as the expert eyes for the PIs, thus freeing them from the burden of being a microgravity environment analyst expert so that they can concentrate on running / analyzing their experiments. It is important to note that the MEMS' main focus is the vibratory regime, but some of the transient activities could be detected as well, depending on the events duration.

MICROGRAVITY ENVIRONMENT

The microgravity acceleration environment of an orbiting spacecraft in a low earth orbit is a very complex phenomenon. Many factors¹, such as experiment operation, life-support systems, equipment operation, crew activities, aerodynamic drag, gravity gradient, rotational effects as well as the vehicle structural resonance frequencies (structural modes) contribute to form the overall microgravity environment. The microgravity acceleration environment, in general, can be considered as made up of three components: quasi-steady, vibratory, and transient components.

Quasi-steady

The quasi-steady component² is composed of those accelerations whose frequency is less than the lowest natural structural frequency of the vehicle. Those accelerations vary over long periods of time, typically longer than a minute. This lowest natural structural frequency depends on the vehicle. For the ISS, the lowest natural structural frequency³ is expected to be around s0.1 Hz. The system configuration and mass properties, the specified altitude, and the attitude control system are the principal contributors⁴ to the quasi-steady accelerations for the ISS.

Vibratory

The vibratory component is composed of those accelerations which are oscillatory in nature and whose frequencies are greater than or equal to the lowest natural structural frequency of the vehicle. They are harmonic and periodic in nature with a characteristic frequency. For the ISS, the characteristic frequencies⁴ of disturbance are expected to be in the range of sub-Hertz to

hundreds of Hertz (0.01 – 300 Hz). The vibratory component includes accelerations caused by equipment operation such as pumps, fans, communication antenna dither motion, centrifuges, and compressors, crew activity, exercise, and structural mode excitations.

Transient

The transient component is composed of those accelerations that last for a short period of time, and are non-repetitive. The transient component includes accelerations caused by the ISS thruster operations, experiment operations, docking and undocking, Intra-Vehicular Activity (IVA), Extra-Vehicular Activity (EVA), and some other crew actions.

Accelerometers

To measure and characterize the microgravity environment on-board the ISS, two primary accelerometer^{5, 6} systems will be used: the Space Acceleration Measurement System II (SAMS-II), and the Microgravity Acceleration Measurement System (MAMS). SAMS-II will measure the vibratory and transient accelerations from 0.01-400 Hz, and MAMS will measure the quasisteady, vibratory, and the transient accelerations to verify the ISS microgravity environment available to the users. Since SAMS II are designated to measure and report the ISS acceleration environment for experimenter teams' use, the PIMS ISS-MEMS will use the acceleration data measured by SAMS-II.

SYSTEM DESIGN STRUCTURE

Since the ISS will be operated in two modes, the ISS MEMS is being developed to characterize both: 1) *Microgravity mode*, and 2) *Non-microgravity* mode. The specification⁴ states that among the capabilities of the microgravity mode is the ability of the ISS to provide the prescribed acceleration environment at a minimum of 50% of the internal user payload locations for 180 days per year in continuous time intervals of at least 30 days, which will be interspersed with reboost and docking events. The following events for the microgravity mode will be characterized: vehicle

structural modes, crew exercise, experiment setup, machinery start up, any long duration thruster firing, and any unknown event, which falls within the prescribed definition of vibratory disturbance sources (Fig. 1). The non-microgravity mode can last between 10 to 25 days after each 30 day microgravity period. The following activities will be characterized for this mode: altitude boost, docking, undocking, EVA, IVA, and any unknown event detected during this mode of operation (Fig. 1).

SYSTEM OPERATIVE MODES

The ISS MEMS is setup to perform both on-line and off-line processing. The on-line processing (Fig. 2) consists of being able to detect all the incoming events the system was trained to recognize (see the soft computing techniques description and PSD data description sections below). In this mode, the system acquires the acceleration data from the ISS downlink and processes it to detect learned patterns. Once the pattern is identified with a certain amount of confidence, the reading is sent to the PIMS-ISS MEMS web site, in near real time, so that all the PIs can see the disturbance sources that might impact the result of their experiments. At that point, the PIs can decide either to continue running the experiment or stop it, if possible.

In the off-line mode (Fig. 3), the system identifies and verifies the patterns, which are unknown to the on-line mode (patterns which have not yet learned by the on-line mode). The on-line mode acquires the pattern and then hands it over to the off-line mode for further processing. This relieves the on-line mode from doing any more guesswork, but instead to focus on its main task, which is to identify the learned patterns. Once the hand-over is done, the off-line mode works in the background. It stores certain features of the unknown pattern such as frequency, acceleration level, time and date the event was identified to a database. The patterns stored in the database are cross-referenced by a PIMS analyst with the ISS data voice loop logbook from the NASA Glenn Telescience Support Center (TSC) as well as with acceleration data analysis to verify if, indeed, a new event (an event which has not yet been

characterized) did take place. If the data voice loop logbook and acceleration data analysis concur, that new event is labeled and classified to match its characteristic frequency. After the accumulation of a number of new patterns in the database, the ISS MEMS is retrained in order to recognize the new patterns as well as the old ones.

SOFT COMPUTING TECHNIQUES DESCRIPTION

At first, the problem to be solved sounds simple enough: identify in near real time the active vibratory disturbance sources, at any time, onboard the ISS from the acceleration data, which are being downlinked from the station. However, once the myriad of other factors are accounted for, complexity arises and soon the problem becomes a very complicated one to deal with. Many factors must be taken into account such as multiple sensors and science racks distributed throughout the science module as well as vibratory disturbance sources located throughout the ISS. In addition, each sensor can be programmed to operate at a different cutoff frequency, which means that some disturbance sources will be measured by more than one sensor (depending on cutoff frequency). Due to the localized nature of the vibratory component, sensor location must be matched with rack location for this monitoring system to be useful to PIs. Finally, not only that the system must classify all the known patterns, in near real time, but also it must recognize the unknown ones as well since the ISS is a new microgravity platform and is being built in increments. As such, some events characteristic frequencies will change from increment to increment until ISS assembly complete. Thus, when all of the factors mentioned above are taken into account, the problem to be solved becomes a complex and difficult one. As a result, several techniques are being combined, each one to tackle a specific aspect of the problem. The following soft computing techniques are used: Kohonen's Self-Organizing Feature Map, Learning Vector Quantization, Neural Networks Back Propagation, and Fuzzy Logic. A brief description of each of the techniques used is given below.

Kohonen's Self-Organizing Feature Map

The principal goal⁷ of the Self-Organizing Feature Mapping (SOFM) algorithm, an unsupervised learning technique, developed by Kohonen is to transform an incoming signal pattern of arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topological ordered fashion. The essential ingredients of such an algorithm⁷ are as follows:

- 1. A one- or two-dimensional lattice of neurons that computes simple discriminant functions of inputs received from an input of arbitrary dimension.
- A mechanism that compares these discriminant functions and selects the neuron with the largest function value
- 3. An interactive network that activates the selected neuron and its neighbors simultaneously
- 4. An adaptive process that enables the activated neurons to increase their discriminant function values in relation to the input signals

Since SOFM is intended only to visualize metrictopological relationships of input, it is not recommended that it be used alone for pattern classification and decision-making. Therefore, the Learning Vector Quantization (LVQ) is used as well.

Learning Vector Quantization

The Learning Vector Quantization⁸ (LVQ) is a supervised learning technique that uses class information in order to improve the quality of the classifier decision regions. The Learning Vector Quantization algorithm is a stochastic approximation algorithm. This algorithm is designed to minimize the possibility of misclassification since it learns to classify input vectors into the target classes specified by the user. More importantly, this algorithm⁹ can be trained to identify classes made up of multiple unconnected regions.

Neural Networks

Artificial neural networks¹⁰ are created to mimic the neural system in human brains. The network consists of many interconnected nodes, similar to neurons in the human brain. Each node assigns a value (known as weight) to the input from each of its counterparts. As these values (weights) are changed, the networks adjust the way it responds. A trained neural network can provide instant mapping from input to output, which simulates the complex behavior of any non-linear system. Since the two techniques described above are used only to classify known patterns, a Back-Propagation Neural Network (BPNN) is used to identify patterns, which are not yet known to the system.

Fuzzy Logic

Fuzzy logic¹¹ is a mathematical technique for understanding, and controlling specific manipulation of continuously variable truthvalues. Fuzzy logic is all about the relative importance of precision since it measures the truth of a given situation as a matter of degree. Between the input and the output, there is a black box that does the work through the use of if-then rules, which embody the knowledge that governs the action of the system that is being described or modeled. Fuzzy logic is used to handle multiple sensors reading for the same event and matched the reading with the racks location and vibrating disturbance sources location (when known) to determine which reading is more relevant to a specific rack. The output of the fuzzy logic is the degree of confidence of which sensor reading is relevant to a specific experiment (rack).

COMBINATION OF THE FOUR TECHNIQUES

SOFM, LVQ, and BPNN techniques are combined into a single module, herein is referred to as Adaptive Pattern Classification and Recognition (APCR). APCR combines three neural network-based techniques, which complement each other. SOFM can group input vectors into several clusters, but can not group clusters into class, nor can it group different clusters into the same

desired target class like LVQ can. This feature (different clusters into the same target class) is very important for both the structural mode excitation and crew exercise events. The structural mode consists of several frequency components spread over a frequency band. The crew exercise has a similar signature with two distinct frequency domain components (body rocking frequency and leg pedaling or footfall frequency). In addition, some vibrating sources exhibit harmonics of their fundamental frequencies. In this case, all the harmonics or the frequency band of a specific event can be lumped into that event target class. SOFM and LVQ can not be used to identify new patterns (unlearned patterns), thus, BPNN is used to detect the new patterns and store them in a database. Finally, when multiple sensors detect the same event, fuzzy logic is used to determine which sensor reading is more relevant to a specific experiment (rack) by using an index known as degree of confidence, which varies from 0 to 1. An index of 1 means that a specific experiment might be impacted (if sensitive to it) by the event that is being tracked by the sensor, while a reading of 0 means no impact.

PSD DATA DESCRIPTION

The Power Spectral Density^{12, 13} (PSD) is a frequency domain function, which is often used to indicate the dominant frequency components present in the data. PSD analysis is performed on time series data to identify the relative magnitudes of sinusoidal signals that compose the series. The basis of this computation is the Fourier transform¹⁴, which indicates the magnitude of each frequency (sinusoid) present in the time history signal. PIMS analysts use the discrete Fourier transform of a time series such that Parseval's relation is satisfied: the RMS of a time signal is equal to the square root of the integral of the PSD across the frequency band represented by the original signal. ISS MEMS uses the PSD data to detect the characteristic frequency of each event using a peak detector algorithm in order to classify all incoming learned patterns (Fig. 4). All unknown patterns are handed over to the off-line mode of MEMS for further analysis.

VISUAL DISPLAY VIA THE WEB

The PI teams will have access to MEMS via the World Wide Web (WWW), where a graphical display will show the status of all the vibratory disturbance sources with their degree of confidence. Both modes (microgravity and nonmicrogravity) will be displayed because even when the ISS is in the microgravity mode, some non-microgravity activities will occur, such as docking, undocking. Figures 5 and 6 show the typical events, which will be displayed for each mode on the WWW. As new events are characterized and added to MEMS, the display will be updated to reflect that. From figures 5 and 6, one can see that each event is named after an expected activity, for example, exercise. Also, there is another label called "HEAD". Once an activity is confirmed to be on (e.g., the x-axis for exercise reads a confidence level of 80%), a PI can click on the label "HEAD" to see where the accelerometer reporting that activity is located. As soon as the PI clicks on that label, a layout of the science module is displayed, showing sensor and rack location (Fig. 7). Obviously, if a sensor head is located close to an experiment, which is sensitive to crew exercise, for example, the PI of said experiment should take appropriate action, whenever possible.

The PIs can also click on any of the three axes associated with a specific event to see a log for that event. Once an event is detected, a log is automatically created, which keeps useful information such as the starting time, average amplitude and frequency, event ending time (Fig. 8). Such a log will be very useful to PIs while analyzing and interpreting their experimental data since it gives them a simplified record of the environment their experiments were exposed to. Knowing the sensitivity of their experiments, they can compare the activity log of an event with any unexplained trend they might come across while analyzing their data to see if such an event correlates with the time segment they are

concerned with. If this log is used appropriately by PIs, it has the potential to accomplish the same function, which had been done in the past by a microgravity environment characterization analyst, albeit it should be used mainly for the vibratory regime.

DISCUSSION AND CONCLUSION

Nihil simul inventum est et perfectum: nothing is created and perfected at the same time. This work does not escape that fate either. What is outlined in this paper lays the foundation upon which the PIMS project will build, improve and fine tune an AI system capable to meet PIs requirements and needs in near real time during ISS utilization. MEMS is being developed to take into account each ISS increment since the characteristic frequency of some events, such as structural modes, is expected to change as the ISS goes from one increment to the next. The soft computing techniques, which are combined for this work to overcome the many technical challenges, at this present moment, are the most suitable combination to accomplish the technical objectives outlined above. As new algorithms / techniques emerge, they will be investigated to see whether they can improve the system.

The main drawback of this system, as is the case with any dynamic system, is the lag time between when an event becomes active on-board the ISS and when the system actually detects said event. The routing of acceleration data from on-board the ISS to PIMS Ground Support Equipment (GSE) located at the NASA Glenn TSC causes such transmission lag time. And once the acceleration data is received, some data processing must be done before any detection / classification can be performed by the system. So, the challenge is how the lag time can be minimized so that the system prediction can become truly "real time". In the near future, several options will be looked into in order to lessen the impact of the lag time. One of them is to process the data in the needed format on-board the ISS before data downlink.

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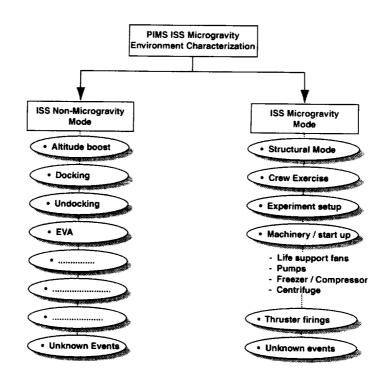


Figure 1. PIMS ISS-MEMS modes and events characterization flowchart

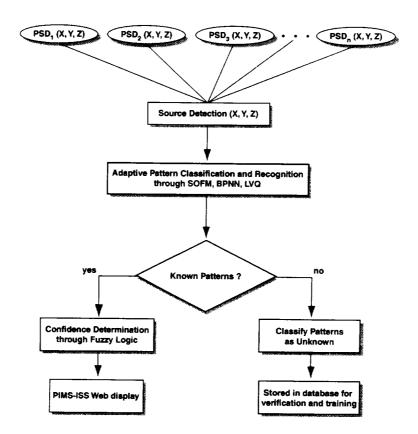


Figure 2. PIMS-ISS overall environment characterization flowchart

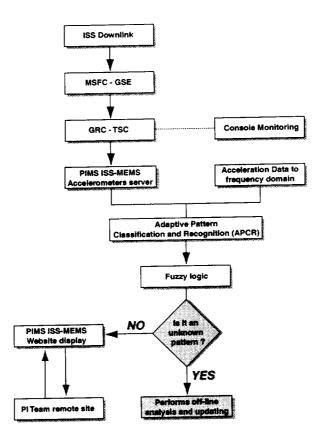


Figure 3. PIMS ISS-MEMS On-line Processing flowchart

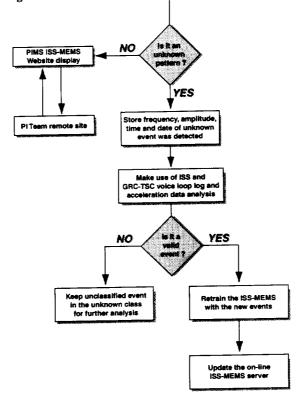


Figure 4. PIMS ISS-MEMS Off-line Processing flowchart

PIMS - ISS Environment Monitoring

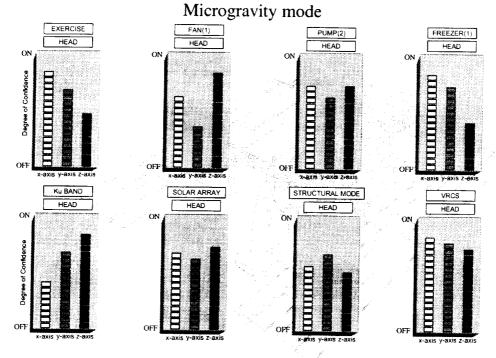


Figure 5. Microgravity mode display

PIMS - ISS Environment Monitoring Non-Microgravity mode

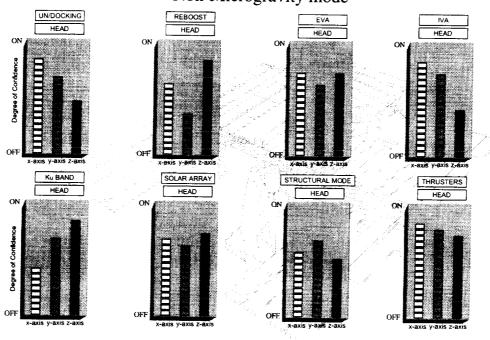


Figure 6. Non-Microgravity mode display

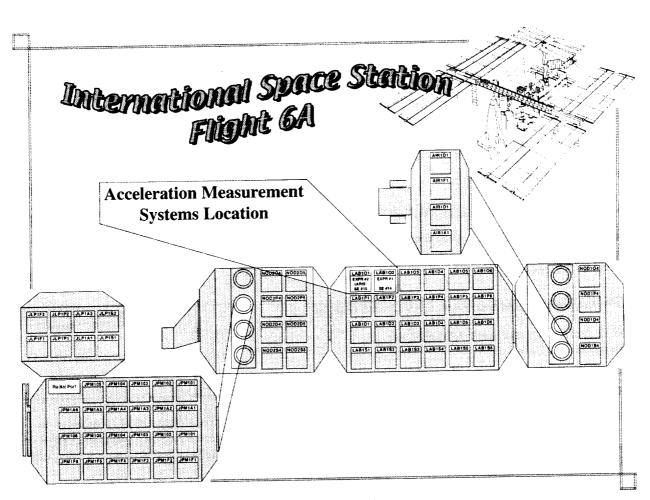


Figure 7. ISS Modules layout

Date: 5/28/00	Head: 1
Time: 00:00:000	Axis: Z
Event Name : Exercise	
Event Start Time: 00:00:000	
Event Ends Time: 00:00:000	
Event Ends Time: 00:00:000	
Event Amplitude /av:	
Event Frequency /av:	
Time Event Reaches Maximu	um Amplitude
Maximum Amplitude :	 / / / / / / / / / / / / / / / / /

Figure 8. Event log

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13. ABSTRACT (Maximum 200 words)

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